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Evaluation of MM5 model resolution when applied to prediction of National Fire Danger Rating indexes

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Abstract. Weather predictions from the MM5 mesoscale model were used to compute gridded predictions of National Fire Danger Rating System (NFDRS) indexes. The model output was applied to a case study of the 2000 fire season in Northern Idaho and Western Montana to simulate an extreme event. To determine the preferred resolution for automating NFDRS predictions, model performance was evaluated at 36, 12, and 4 km. For those indexes evaluated, the best results were consistently obtained for the 4-km domain, whereas the 36-km domain had the largest mean absolute errors. Although model predictions of fire danger indexes are consistently lower than observed, analysis of time series results indicates that the model does well in capturing trends and extreme changes in NFDRS indexes.

Introduction

The purpose of the present research was to couple the National Fire Danger Rating System (NFDRS) with the MM5 meteorological model, to provide NFDRS predictions at grid points over the full landscape within the domain of the model, and to evaluate the value of decreasing grid cell spacing in the modeling process. The NFDRS was developed in the 1970s to provide indicators of fire severity based on weather and fuel conditions and thereby help fire managers make decisions and plan for staffing and resource management in the control of wildfires (Deeming *et al.* 1977; Burgan 1988). Traditionally, NFDRS observations and forecasts have been made at locations considered to be representative of the fuels and climatology in a broad area. With high-speed, high-resolution modeling becoming more affordable and timely, it may be possible to produce NFDRS predictions on hourly time scales and at spatial resolutions that may be useful for application in both fire danger rating and fire behavior prediction. The present paper documents some first steps in that direction. In addition to developing techniques for applying modeled weather data to NFDRS predictions, a case study of an extreme fire season is used to test the predictions and to compare predictions from three different model domains.

Data and model simulations from the 2000 fire season in North Idaho and Western Montana were used to develop and evaluate automation of predicted NFDRS indexes. A case study approach was used in order to evaluate the usefulness of predictions as applied during a period of known high fire danger. Because NFDRS values are most critical under extreme conditions, data sample points within mapped fire perimeters were used in order to ensure the model was tested for performance in areas where actual fires occurred. Evaluation of the results for the 36-km, 12-km, and 4-km domains was done by comparing model output with NFDRS observations in three different ways: (1) averaged within fire weather zones as defined by land managers in coordination with National Weather Service fire weather meteorologists; (2) interpolated over the landscape; and (3) at the closest available Remote Automatic Weather Station (RAWS).

NFDRS indexes calculated on different fuel models vary differently with incremental changes in the weather. Fuel models mapped to grid cells may be different at any given point from the fuel model at the same point at a different spatial resolution. Gridded fuel models may also be different from what is observed on the ground. Thus it is difficult to compare point to point predictions in a meaningful way using

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spatially varying fuel models. To remove such complexities, all computations for both observations and model predictions were done using fuel model G (short-needle conifer with heavy dead fuel load). This had the effect of holding the fuels constant while allowing weather, fuel moisture, and slope to vary. This provides a more meaningful comparison between predictions for the same location, which might otherwise be based on different fuel types where grid cell spacing differs.

Background

The NFDRS integrates fuels, topography, and weather data to generate fire danger indexes. Manual observations taken once a day have, for the most part, been replaced by RAWS, which collect hourly weather data. However, NFDRS is calculated only once a day in mid-afternoon (1300 LST) to estimate the upper bound of fire danger when conditions are usually the hottest and driest.

Through the Fire Consortia for Advanced Modeling of Meteorology and Smoke (FCAMMS), many modeling centers are now running high-resolution mesoscale models to produce regional weather predictions on a real-time, operational basis. These mesoscale models can generate the meteorological fields necessary to calculate NFDRS indexes. This opens the door for providing fire managers with fire danger predictions at a finer temporal and spatial resolution than has ever been available. The present research takes a first step in examining the usefulness of such fine-scale predictions when applied to an extreme fire season.

Modeling the NFDRS

A case study run of the MM5 was used to simulate the 2000 wildfire season in the Northern Rocky Mountains and calculate the predicted daily NFDRS fields. For a more detailed background on the case study, see Hoadley *et al.* (2004). The case study area contained three nested modeling domains: an outer 36-km grid, an intermediate 12-km grid, and an inner 4-km grid (Fig. 1). Four NFDRS indexes, Energy Release Component (ERC), Spread Component (SC), Burning Index (BI), and Ignition Component (IC), were computed on all three grids to determine the preferred grid cell spacing for fire danger predictions. ERC is an index of the available energy per unit area within the flaming front of the fire, and depends on fuel moisture. SC is a measure of the forward rate of spread of the fire, and is sensitive to wind speed, slope, and 1-h fuel moisture. BI is an indicator of the difficulty of containment, and is a combination of ERC and SC. IC is an index of the probability a firebrand will start a fire requiring suppression activities, and is affected by SC and 1-h fuel moisture.

Traditionally, the NFDRS indexes have been computed from weather data collected at point locations. The topography and fuels information are determined once for each location, leaving only weather data to be obtained once a day. Similarly, in calculating NFDRS indexes with modeled weather at every grid cell (rather than at widely spaced observation sites), the topography and fuel information can be determined once for each grid cell, with only the meteorology changing every day. Therefore there are several 'static' gridded fields that are used in the index calculations. These constant fields include the terrain slope, and maximum and minimum Normalized Difference Vegetation Index (NDVI) grids, which are used for estimating live fuel moisture (Burgan and Hartford 1993, 1997; Burgan *et al.* 1996). NDVI data are derived from satellite observations obtained with the Advanced Very High Resolution Radiometer (AVHRR) sensor.

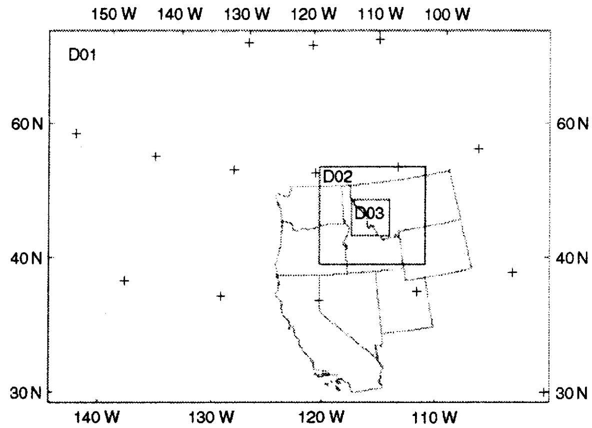

Fig. 1. Modeling domains. D01 is 36-km resolution, D02 is 12-km resolution, and D03 is 4-km resolution.

Modifications to NFDRS equations

Because model-generated predictions, rather than observations, are used to compute the NFDRS indexes, some modifications to the equations are required. Specifically, there are differences in the way some fuel moistures are computed. The smaller dead fuel elements (1-h and 10-h fuels) respond very quickly to weather changes; therefore, the small dead fuel moistures can be calculated using the same equations as the traditional NFDRS, and prediction errors do not propagate with time. The larger (100-h and 1000-h) fuels respond much more slowly to changes in atmospheric conditions and are modeled by daily boundary conditions of maximum and minimum temperature, relative humidity, and hours of precipitation. Consequently, the equations for 100-h fuels keep track of weather conditions over the past 24 h, whereas the 1000-h equations keep a memory of the weather variables over the past 7 days. Additionally, both of the larger fuel classes are sensitive to day length. Because of the effect of the previous weather on these large fuels, it is necessary to 'nudge' the automated NFDRS process daily with observed data to keep errors in the 24-h boundary conditions from accumulating in the large fuel moisture computations.

Observed values of fuel moisture from the previous day were used as the 'initial' value to compute fuel moisture for the prediction day. For the case study, the archived RAWS point data were obtained and interpolated to each of the three MM5 domains using Cressman's interpolation scheme (Cressman 1959). One additional daily grid required to compute the indexes is the Keetch–Byram Drought Index (KBDI). KBDI was also available from the archived RAWS data and interpolated to the MM5 domains using the Cressman scheme.

Preparation of gridded input fields

Live fuel moisture in the predicted NFDRS implementation is estimated from relative greenness (RG) maps, which are derived from NDVI. These maps depict how green the vegetation is in each grid cell relative to how green it has been historically (1989–1995). New relative greenness maps on the 1-km full-US grid are available for downloading from the Wildland Fire Assessment System (WFAS) once a week. Archived RG maps were used for the case study.

The US 1-km grids of NFDRS input fields such as fuel moisture and relative greenness use a Lambert Azimuthal projection, and have 2889 rows and 4587 columns. The MM5 domains used in the present study use a Lambert Conformal Conic projection. The 36-km domain has 126 rows and 150 columns, the 12-km domain has 111 rows and 150 columns, and the 4-km domain has 219 rows and 204 columns. Therefore, all the 1-km grids were re-projected and re-sampled to be geographically aligned with the MM5 grids.

After the static grids were all re-projected to the MM5 domains, the necessary meteorological fields were extracted from the MM5 output files for each day. The model run initialized at 0000 UTC each day was used to generate the NFDRS predictions. The NFDRS indexes were calculated for the period from 1500 Mountain Daylight Time (MDT) to 1500 MDT the following day (forecast hours 21 through 45). The index calculations require fields of temperature, relative humidity, wind speed, and cloud cover at 1500 MDT (forecast hour 45), and the previous 24-h (forecast hours 21 through 45) fields of maximum and minimum temperature and relative humidity, precipitation amount, and precipitation duration.

Because model data, rather than observations, were used to compute the indexes, two of the input variables obtained from the model were handled differently than the data obtained from RAWS sites. Cloud cover, a variable not predicted by the model, is required for NFDRS calculations. The MM5 does, however, compute incoming shortwave (SW) radiation, which was used to estimate cloud cover. For each day, the maximum possible incoming SW radiation was computed at the center of each grid cell in all the domains, based on time of day and latitude and longitude of the grid cell. These computations were based on the following equation:

$$\mathrm{qs} = \mathrm{qa}(\mathrm{a} + \mathrm{b} \times \mathrm{cloudfrac}),$$

where qs = actual SW radiation reaching the earth's surface (from MM5), qa = extraterrestrial SW radiation (computed from latitude, date, and time), 'a' ranges from 0.18 to 0.4 (a mean of 0.27 was used), 'b' ranges from 0.42 to 0.56 (a mean of 0.52 was used), and cloudfrac = 1 if clear, 0 if cloudy (Maidment 1993). The percentage of sky covered by cloud was estimated by solving for cloudfrac.

The second variable modified was precipitation duration (number of hours in the past 24 h when precipitation occurred). The MM5 predicts convective and non-convective precipitation. One characteristic of the convective parameterization is that it tends to over-predict convective precipitation in the summer. If there is a small probability of convective rainfall, the model predicts trace amounts of precipitation over large areas for several hours. Consequently, some days were found when a significant number of grid cells in the domain had up to 24 h of precipitation predicted, even though the amount was little more than a trace. To rectify this problem, a minimum of 1.3 mm (0.05 inch) of convective rainfall in an hour was required before that hour was added to the duration total. To include cases when convective rainfall was less than 1.3 mm for any single hour in a day but accumulated to more than 1.3 mm over the 24-h period, at least 1 h of rainfall was counted whenever the 24-h total was greater than 1.3 mm. Because the MM5 more accurately predicts the duration of non-convective rainfall, any amount of non-convective rainfall was included in the totals for both precipitation duration and amount.

Evaluation results

NFDRS observations are taken at point locations whereas our automated fields were output to grids at 36, 12, and 4 km. This presented some challenges for objective evaluation. Because fire danger ratings are intended to be applied over a large geographic area (Schlobohm and Brain 2002), observations were aggregated by: (1) averaging over fire weather zones (zonal averaging); and (2) interpolation using an inverse distance square scheme in ESRI's ArcGIS software (ESRI, Redlands, CA, USA). The closest available RAWS observation to each fire was also considered, however, to allow comparison with the results for zonal averaging and interpolated observation fields.

Each of the three mapped observation fields was overlaid with mapped output grids at each of the three domains in ArcGIS, and data were extracted from within the study fire perimeters (or the closest RAWS). In cases where fire perimeters overlapped more than one grid cell or fire weather zone, the highest observed or predicted value within the fire perimeter was recorded for evaluation.

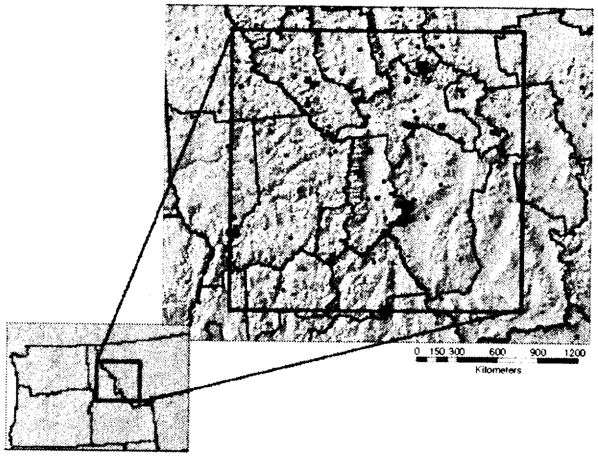

Fig. 2. Map showing fire weather zones (thin dark grey lines), Remote Automatic Weather Stations (RAWS) (grey dots), study fire area burned (black shapes), and RAWS closest to study fires used for evaluation (dark grey squares).

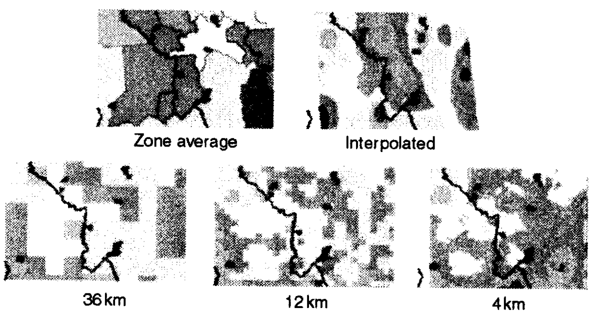

Fig. 3. Mapped values of Energy Release Component for 30 July 2000. Lower values are represented by light colors and higher values by darker colors. Heavy black lines show the border between Idaho and Montana. Black shapes are fire perimeters used as sampling points for data extraction.

Zonal averages were achieved using ArcView Spatial Analyst to average the observed NFDRS indexes from all available RAWS stations within a fire danger rating area for each day. Fire danger rating areas, also referred to as fire weather zones, are areas of generally homogeneous fuel, weather, and topographic features and may be tens of thousands of acres in size (Schlobohm and Brain 2002). In the western USA, these zones are generally defined collaboratively by land managers and fire weather meteorologists. Fire weather zones for the study area are shown in Fig. 2. ArcView Spatial Analyst was also used to compute interpolated values. For all available RAWS stations, an inverse distance-weighting scheme was applied to arrive at interpolated values across the landscape for each index each day. Figure 3 shows a typical pattern for zone-averaged and interpolated ERC data, as well as grid patterns for each of the three model domains.

Six fires or complexes were selected for the evaluation, based on the size and duration of the fire as well as the existence of adequate geographic information system mapping of the fire perimeter through the life of the fire. Table 1 provides a summary of the size and duration of each fire. Figure 4 shows the relative size and location of these fires. Data were extracted from the model grids overlaid with fire perimeters. Because NFDRS is intended to identify the worst-case scenario, if more than one grid cell value occurred within a fire perimeter, the highest value was selected for evaluation purposes.

The six fires and a 30-day study period (26 July through 24 August 2000) produced 168 prediction and observation pairs. Although the fires started on different dates within the study period, predictions were evaluated for the entire 30 days at each fire location.

Because observed and predicted values of SC varied only in very small increments during the study period, SC was not included in the evaluation. Discussions with NFDRS experts at the Missoula Fire Laboratory indicated that this is normal and that, in general, SC is not widely used by fire managers. It is also likely that the wet bias of the MM5 resulted in very low values because of the influence on fine fuel moisture.

For each index, mean error (ME), mean absolute error (MAE) and root mean square error (RMSE) were computed to measure the accuracy of the predictions. ME, also called bias, is the average of the difference between the prediction and observation:

$$\left(\sum(\mathrm{P}-\mathrm{O})\right)/\mathrm{N},$$

where P = the highest predicted value within a fire perimeter, O = the highest observed value within a fire perimeter, and N = the number of sample pairs. ME gives an indication whether, on average, errors are more likely to be positive or negative but, because the positives and negatives cancel each other out, ME does not tell us much about the average size of the error. MAE averages the absolute value of the errors $((\sum|\mathrm{P}-\mathrm{O}|)/\mathrm{N})$ and is a better indicator of the size of the error but tells nothing about the sign of the error. RMSE is calculated by computing the average of the squares of the errors and then finding the square root (SQRT $([\sum(\mathrm{P}-\mathrm{O})^2]/\mathrm{N})$). This statistic gives an indication of the tendency for large errors to occur. In general, the RMSE scores in the present study were similar in magnitude to the MAE scores, indicating that individual large errors were not influencing the statistics. Therefore, RMSE errors are not presented in the discussion.

Energy release component

ERC is a number relating to the available energy per unit area within the flaming front at the head of a fire. It is expressed as an index value but can be related to units of the order of 450 J/m^2 (British thermal unit/ft^2 divided by 25). ERC is based solely on variations in fuel moisture (Schlobohm and Brain 2002).

Table 1. Study fire information

Fire/complex name	Location	Start date	Contained	Acres burned
Monture/Spread Ridge	Lolo NF	13 July	6 September	27 500
Mussingbrod	Beaverhead/Deer Lodge NF	31 July	26 September	84 939
Blodgett Trailhead	Bitterroot NF	31 July	10 September	11 276
Ryan Gulch	15 miles E of Clinton, MT	7 August	30 August	17 118
Thompson Flat	Lolo NF	4 August	8 September	14 396
Burnt Flats	Clearwater NF	11 August	1 September	22 527

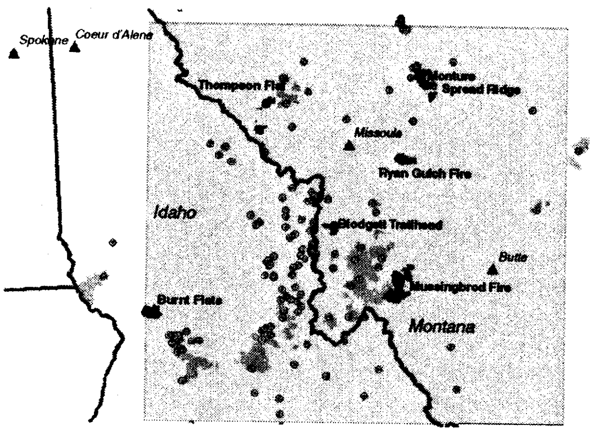

Fig. 4. Location of 2000 wildfires within the 4-km domain (shaded). Burned area of all fires is shown by darker grey shading and study fires are shown in black. The circle-with-dot symbols show location of all fires; owing to the map scale, smaller fires will not show burned area. Solid black triangles are major cities, and solid black lines are state boundaries.

Table 2. Mean error (ME) and mean absolute error (MAE) of predicted energy release component

Statistic	Domain 36-km	12-km	4-km
ME			
Interpolated	−17.46	−14.20	−6.99
Closest	−19.45	−16.19	−8.98
Zone	−9.43	−6.17	1.04
MAE			
Interpolated	18.59	15.65	11.16
Closest	21.61	18.62	14.34
Zone	11.67	8.89	6.45

In a previous evaluation of meteorological parameters predicted by MM5 using the same case study, it was found that the model-predicted relative humidity values were generally too moist (Hoadley *et al.* 2004). Because relative humidity directly influences fuel moistures, which are the primary influence on ERC, it was expected that predicted ERC values would be low. Table 2 shows the ME and MAE statistics for ERC in all three domains using three different approaches to interpreting observed values. In general, the ME is negative as expected, indicating predicted ERC values lower than observed. When observations were averaged over fire weather zones, however, the 4-km domain showed a slight positive bias, indicating predicted values higher than observed. Also, ME scores of the 4-km results showed greater accuracy than those of the other domains regardless of observation strategy. The MAE results indicate that all domains are better at predicting the zonal average and the 4-km domain consistently has the least error. During the study period, the observed ERC at RAWS stations closest to the study fires had values generally ranging from the mid-50s to low 90s. The range from minimum to maximum observed ERC at any one station during the study period was as little as 13 points on the Thompson Flat and Burnt Flats complexes, to as much as 36 on the Ryan Gulch Fire. MAE for predicted ERC of the magnitude observed in this study may be unacceptable for fire operations given that they represent a high percentage of the seasonal variability. It may be necessary to develop techniques to remove the bias in order to make them more meaningful for practical application.

Figure 5 shows a pocket card for the Bitterroot National Forest. Pocket cards were developed as a tool for firefighters to gauge the severity of the current fire season against average and extreme years. The graphics show seasonal variability of ERC. From this, one can see that the difference between an average and an extreme year at this location is of the order of 15 points of ERC, so underpredicting ERC values by 15 points could be very misleading in assessing the actual fire danger.

Figure 6 shows a time series of the observed and predicted indexes for two of the study fires graphed against the daily acreage increase of the fire. Although there are many factors influencing the growth of a fire, and a correlation with NFDRS indexes is not expected, it is interesting to consider whether there might be an observable relationship between fire growth and NFDRS indexes. In general, the predicted values of ERC capture the overall trend of the observations for the two fires shown. The predictions show considerably more variability, however. This is likely due to over-prediction of precipitation.

Burning index

The BI combines SC and ERC to provide a number that relates to the difficulty of controlling a fire owing to fire behavior. Values of BI have units that approximate 10 times

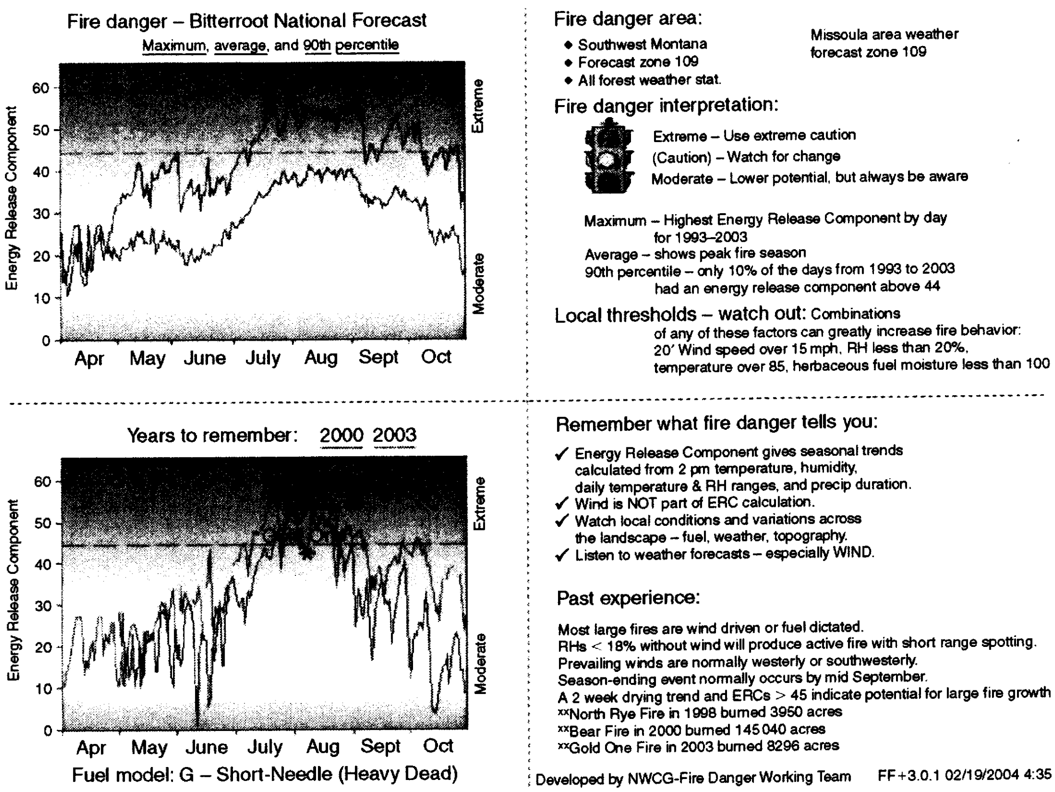

Fig. 5. Pocket card for the Bitterroot National Forest showing seasonal variability of Energy Release Component for average and extreme years.

the flame length in feet. The scale is open ended. BI is sensitive to changes in wind speed, slope, and relative humidity (Schlobohm and Brain 2002). MM5-predicted values of BI are expected to be low owing to the bias in relative humidity seen in an earlier study (Hoadley *et al.* 2004). Table 3 shows the ME statistics for BI. Not only are the results negative as expected, indicating predicted values lower than observed, but the average errors are quite large. Errors of −40 for BI imply that flame lengths are underestimated by 1.2 m. This can mean a significant difference in tactics or even in the ability to use direct attack strategies on a fire. Because fireline intensity increases more than twice as fast as flame length, the underpredicted values of BI give an even more distorted view of potential fire behavior. All three domains do a better job of predicting the zonal average and once again the 4-km domain has the consistently best performance of the three. Figure 6 shows time series data for BI for two fires during the study period.

Ignition component

The IC is a rating of the probability that a fire requiring suppression action will ignite given that an ignition source is present. IC is sensitive to variations in wind and fine fuel moisture. IC is expressed as a probability and has values ranging from 0 to 100 (Schlobohm and Brain 2002). Earlier analysis showed that the MM5 performed reasonably well in predicting wind speeds (Hoadley *et al.* 2004). Thus, any errors in predicted IC should be attributed to errors in the predicted relative humidity. High relative humidity predictions would cause the fine fuel moisture values to be too high, resulting in too low values of IC.

Table 4 shows the ME and MAE statistics for IC. As expected, based on the model predictions of relative humidity, the results show that predicted values of IC are consistently lower than observed. As with ERC, the 4-km results are consistently better than the other domains. However, errors of 19–29% of the full range of values for IC should be considered too large for operational requirements. It may be possible to develop a simple filter to bring the predicted values into an acceptable range for operational use by adjusting for known biases in the model. Figure 6 shows a time series of IC for two of the study fires.

Discussion

Predicted grids of NFDRS indexes using the MM5 mesoscale model output have been created. The predictions were evaluated using a sample of points extracted from actual fire locations, and compared with observed NFDRS values

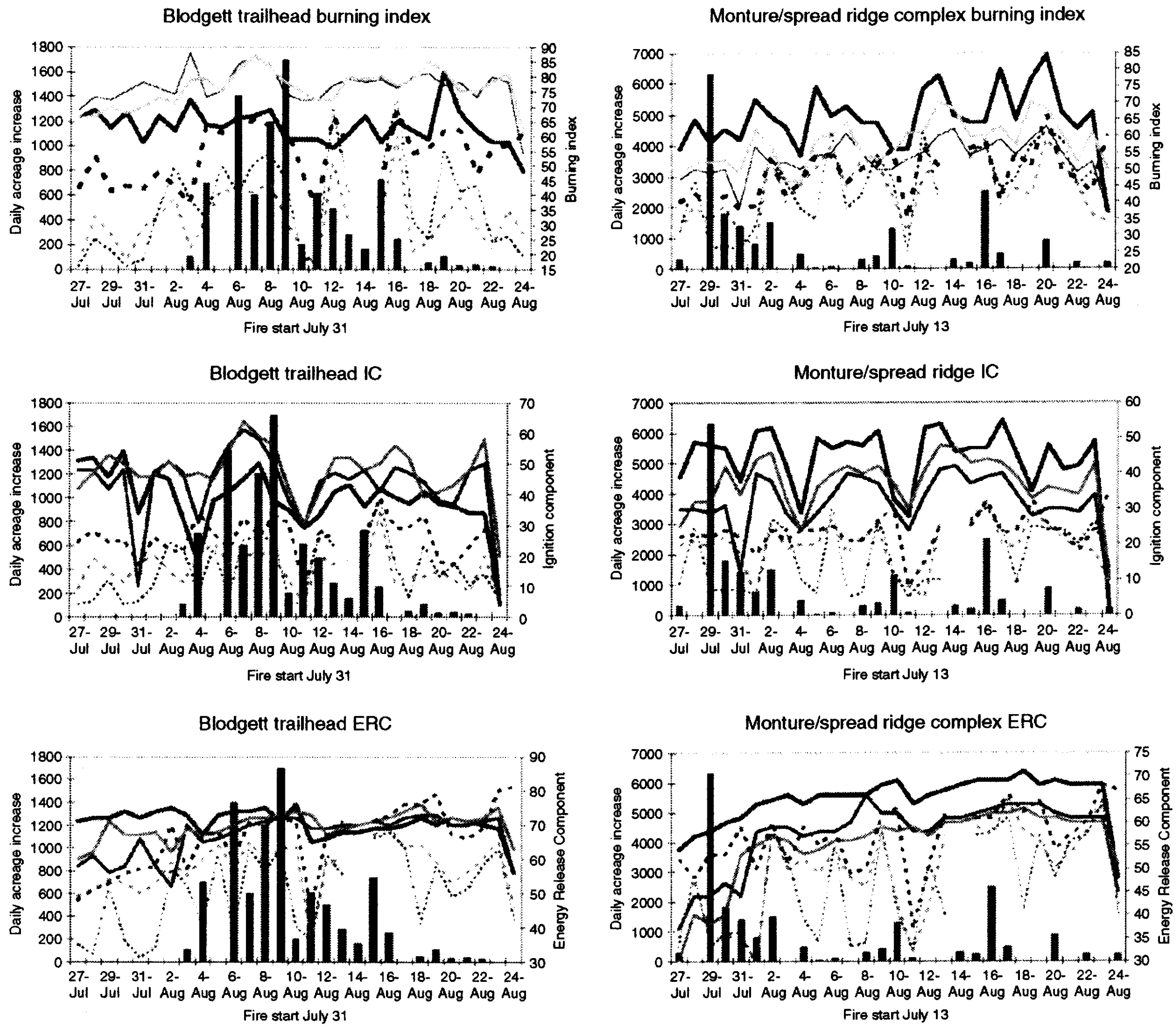

Fig. 6. Time series charts of observed (solid lines) and predicted (dashed lines) National Fire Danger Rating System indexes for two of the study fires. The closest Remote Automatic Weather Station observation is shown by the heavy black line, the zonal average by the thin black line, and the interpolated value by the heavy grey line. Predicted data includes 36-km resolution shown by the thin dashed black line, 12-km resolution by the dashed grey line, and 4-km resolution by the heavy black dashed line. For reference, only daily increase in fire acreage is indicated by the black bars.

Table 3. Mean error (ME) and mean absolute error (MAE) of predicted burning index

Statistic	Domain		
	36-km	12-km	4-km
ME			
Interpolated	−41.00	−40.89	−33.08
Closest	−40.40	−40.29	−32.48
Zone	−27.27	−27.16	−19.35
MAE			
Interpolated	41.15	40.96	33.61
Closest	42.12	41.02	35.28
Zone	27.95	27.40	20.82

Table 4. Mean error (ME) and mean absolute error (MAE) of predicted ignition component

Statistic	Domain		
	36-km	12-km	4-km
ME			
Interpolated	−33.17	−31.02	−26.80
Closest	−32.39	−30.25	−26.02
Zone	−23.31	−21.17	−16.94
MAE			
Interpolated	33.24	31.38	28.06
Closest	33.14	31.08	28.71
Zone	23.49	22.08	19.21

calculated at the closest observation point, an interpolation of all available observations, and observations averaged by fire weather zone. Not surprisingly, certain biases in the model are reflected in the NFDRS predictions, especially when relative humidity is a significant influence. When comparing the three model domains, the 4-km results are consistently better than either the 12-km or the 36-km results for all indexes and all observation strategies. The 36-km results are consistently the least reliable for all indexes. The model does a much better job of predicting zone averages than interpolated values or point observations. This indicates that the smoothing that occurs with zone averaging may mask fine scale errors arising from coarse terrain or boundary layer conditions in the model. The size of errors would indicate that until further refinements are made in the modeling system, these predictions should be used with caution and are not suitable for detailed application in an operational environment. However, these predictions may be useful for broad scale analysis of trends in fire danger and comparisons between geographic areas where the user is only interested in relative differences and not hard values. It is also possible that in a less extreme fire season, the results would be more realistic for operational applications because the model would be expected to have more realistic predictions of relative humidity (Hoadley *et al.* 2004).

Improvements in the implementation of MM5 real-time predictions in the Pacific Northwest to mitigate the modeled bias in relative humidity and temperature are planned. This should provide better predictions of the NFDRS indexes. Also, as the MM5 is replaced by the Weather and Research Forecast model, there will be more opportunities for improvements in NFDRS model predictions. The Weather and Research Forecast model will have more options for boundary layer and land-use schemes, which may provide more realistic temperature and relative humidity predictions during quiescent, stagnant periods of concern to fire weather forecasters.

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